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TECHNOLOGY INVESTMENT ADVISOR: An Options-Based Approach to Technology Strategy

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ABSTRACT: Recent years have seen increased efforts to link technology strategies to business strategies, which requires expressing returns on technology investments in terms of business impacts. These impacts are usually many years in the future and highly uncertain. These factors are typically addressed by applying discounted cash flow methods to valuing alternative investments. This approach often shows long-term technology investments to be of low present value because of the compounding of the discount rate several years into the future. Proponents of such investments often counter this heavy discounting by inflating projections. This debate can be recast by defining the purpose of technology investments, and the R&D efforts enabled by these investments, to be creation of options for achieving business results, not necessarily for creating business results directly. This article develops and illustrates this approach in terms of integrated models for options pricing, market/technology maturity, production learning, and competitive scenarios. These models are embodied in the *Technology Investment Advisor*, a computer-based tool that supports formulation and evaluation of technology strategies.

INTRODUCTION

Recent years have seen increased efforts to link technology strategies to business strategies, whether the "business" be for-profit, non-profit, or government. Consequently, proponents of technology investments are required to express returns on these investments in terms of business impacts. These impacts are usually many years in the future and highly uncertain. Typically, investment analysis addresses these factors by applying traditional discounted cash flow methods to valuing alternative investments. This approach to investment analysis often shows long-term technology investments to be of low present value because the compounding of the discount rate several years into the future results in projected cash flows in those years being severely reduced in value. Proponents of such investments often counter this heavy discounting by inflating projections to compensate for the small weightings applied to out-year returns.

This debate can be recast by redefining the purpose of technology investments and the R&D efforts enabled by these investments. Many large enterprises make long-term technology investments for the purpose of creating options for achieving business results, not for creating business results directly. Many first-rate, long-term R&D efforts, especially research efforts, will never substantially impact the business returns motivating the original investment. However, the options created by these efforts have intrinsic and possibly quite substantial value to the enterprise. From this perspective, the purpose of these investments is to create viable technology options, most of which will not be exercised but are, nonetheless, of significant value. This perspective dramatically changes how investment analysis should be pursued.

This paper introduces a new approach to investment analysis and, thereby, a new approach to technology strategy. This approach builds upon a number of models:

- Options pricing (Black–Scholes) models which enable valuation of downstream cash flows due to contingent investments in bringing technologies to market
- S-curve models of market/technology maturity to represent the process of launching market offerings to create these cash flows
- Production learning models to represent the impact of cumulative production experience on unit costs
- Competitive scenario models that reflect the impacts of competition on likely ranges of market shares and profit margins.

These models are embodied in a computer-based tool, the *Technology Investment Advisor*, that enables flexible integration of these models to support both formulation and evaluation of technology strategies. The next section of this article outlines an overall approach to investment analysis and then reviews the above models and how they fit within this approach. The *Technology Investment Advisor* is then described, followed by an example to illustrate how the various models work together and typical insights that result.

APPROACH

The purpose of this approach is to project the impacts of technology investments, primarily in R&D, and quantify the value of these impacts. In other words, this approach supports addressing two fundamental and related questions:

1. For alternative investments under consideration *in the present*, what are the likely impacts of these investments *in the future*?
2. Given likely *future impacts* of alternative investments, what *current value* should be attached to these future impacts?

As shown in Figure 1, these two questions can be addressed in either order. The above order — that is, first No. 1 and then No. 2 — assumes that one starts with the alternative investments, projects their impacts, and then determines the valuation of these impacts. The reverse order — first No. 2 and then No. 1 — involves starting with desired/needed future impacts and working backwards to determine the implications for current investments. The approach described in this article supports pursuing technology investments in either order.

Underlying Difficulties

Before explaining how this approach helps address these questions, it is useful to consider why these questions pose difficulties. Put simply, the future is usually years from now and it also tends to be highly

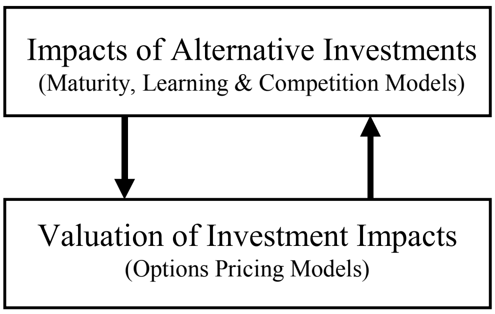

Fig. 1. Two approaches to investment analysis.

uncertain. Thus, returns on technology investments are both delayed and uncertain. This can make it difficult for these investments to compete for resources with alternatives that provide nearer-term, more certain returns.

However, most people recognize the need to have near, mid, and long-term technology projects in their overall portfolio of investments. At the very least, they want to avoid clogging the pipeline with too many projects maturing at the same time. More importantly, they recognize that the long-term will eventually become the near-term and there must be mature technologies to exploit at that time.

Nevertheless, returns today are worth more than equivalent returns tomorrow. Similarly, returns that are risk-free are worth more than returns that are risky, assuming the same expected values for both alternatives — and, assuming that investors are not risk-prone. Traditionally, investment analysis has relied on discounting future returns, in part to reflect the cost of capital for the investment and in part to hedge against risks and uncertainties.

This discounted cash flow approach to investment analysis often shows long-term technology investments to be of low present value because the compounding of the discount rate several years into the future results in projected cash flows in those years being severely discounted. Proponents of such investments often counter this heavy discounting by inflating projections to compensate for the small weightings applied to out-year returns.

As a result, what was supposed to be an objective analysis becomes highly subjective with the risk avoiders pushing for high discount rates and the risk takers projecting inflated returns to compensate for these discount rates. The approach presented in this article provides the means for avoiding such self-defeating arguments. It does this by representing investment decisions in ways that more appropriately reflect the true nature and roles of technology investments in assuring future competitive market positions (Amram & Kulatilaka, 1999; Coy, 1999).

Technology Options

Investing in technology is not the same as investing in facilities or equipment. The purpose of technology investments — especially research investments — is to create alternatives that investors can subsequently have the option of exploiting. Whether they choose to exploit these alternatives depends on factors such as the likely competitive advantage provided, projected market demand, and emerging technology standards. These factors tend to become clearer as time passes.

In this way, technology investments provide options that investors can subsequently choose to exercise — or not. Often, exercising an option involves investing in further development, equipment, facilities, and so on. Thus, the investment needed to exercise an option may be much larger than the investment needed to create an option. However, the decision to make this larger investment is contingent on improved knowledge of a variety of factors — knowledge that is inherently unavailable when the original technology investment is made.

Traditional investment analysis is not well suited for addressing investments that have an initial investment and a later investment that is contingent on factors that will not be known until the later time when the contingent decision is to be made. Options pricing models provide a means for representing this type of decision-making problem.

Options Pricing Model

Succinctly, options pricing models are concerned with investments that are made to create the potential for possible future investments for which subsequent returns are likely[1]. As noted earlier, investments in

[1] These models were originally developed in the early 1970's for establishing the value of stock and commodity options. They have only recently been adopted for valuation of technology investments.

R&D efforts are often made to create the intellectual property and capabilities to subsequently decide whether or not to invest in launching new products or services. The initial investments amount to purchasing options to make future investments and earn subsequent returns. These options, of course, may or may not be exercised.

Amram & Kulatilaka (1999), Boer (1998, 1999) and Luehrman (1998) advocate using options pricing models to analyze this type of investment situation. Options pricing models focus on establishing the value of an option to make an investment decision, in an uncertain environment, at a later date. Equations 1–3 summarize the basic calculations as outlined by Luehrman.

The NPV (Net Present Value) Quotient is formed as the ratio of the Present Asset Value — that is, the traditional NPV of the free cash flow projected to result from exercising the option — and the present value of the investment required to acquire these assets, i.e., the Option Exercise Price, X. As shown by equation 2, the latter present value decreases as the risk-free rate of return increases and/or the time increases until the option must be exercised, or it expires.

$$\text{NPV Quotient} = \text{Present Asset Value}/\text{PV}(X) \tag{1}$$

$$\text{PV}(X) = \text{Option Exercise Price}/(1 + r_f)^t \tag{2}$$

The use of a risk-free rate is premised on the assumption that PV(X) will be invested now and accrue interest at rate r_f for t time periods so that the exercise price, X, will be available when the option can be exercised. The risk-free rate is used because these funds are not at risk until investors decide to exercise the option. If they choose to let the option expire, they retain X for other purposes.

Also important is the Cumulative Volatility expressed, as shown in equation 3, as the product of the standard deviation of returns per period times the square root of the number of periods.

$$\text{Cumulative Volatility} = \sigma\sqrt{t} \tag{3}$$

σ^2 is the variance of returns per time period, and t equals the number of time periods. The inclusion of volatility in options pricing models is central to realistically representing investments where it is seldom the case that future returns are certain.

Note that σ^2 is assumed constant with time, t, although equation 3 does show the cumulative variability increasing with time. One might argue that the variance will, in general, vary with time. However, such variations would be very difficult to empirically assess and the resulting formulation would not admit to as straightforward a solution. Sensitivity analysis and Monte Carlo analysis, as discussed later in this article, enable explorations of the impacts of different assumptions regarding σ^2.

The values of the NPV Quotient and Cumulative Volatility are used to ascertain Black–Scholes values which are computed from, not surprisingly, the Black–Scholes options pricing model (Black & Scholes, 1973). As shown in Figure 2, these values, expressed as percentages, increase with increasing NPV Quotient and increasing Cumulative Volatility. This percentage is multiplied times the Present Asset Value, in equation 1, to determine the value of the option.

Looking at this figure, the value of an option to later decide on an investment would seem to increase with r_f, σ^2, and t. In particular, in the presence of high volatility and high risk-free returns, it would seem that the longer one can wait to decide, the more valuable the option. However, the Present Asset Value in equation 1 decreases with time. Thus, depending on the specific cash flow and investment projections, as well as the parameters chosen, the option value may increase, decrease, or possibly increase to a maximum and then decrease. Sensitivity analysis is a good way to gain an understanding of this range of possibilities.

The resulting option value is totally premised on the assumption that waiting does not preempt deciding later. In other words, the assumption is that the decision to exercise cannot be preempted by somebody else deciding earlier. In typical situations where other actors (e.g., competitors) can affect possible

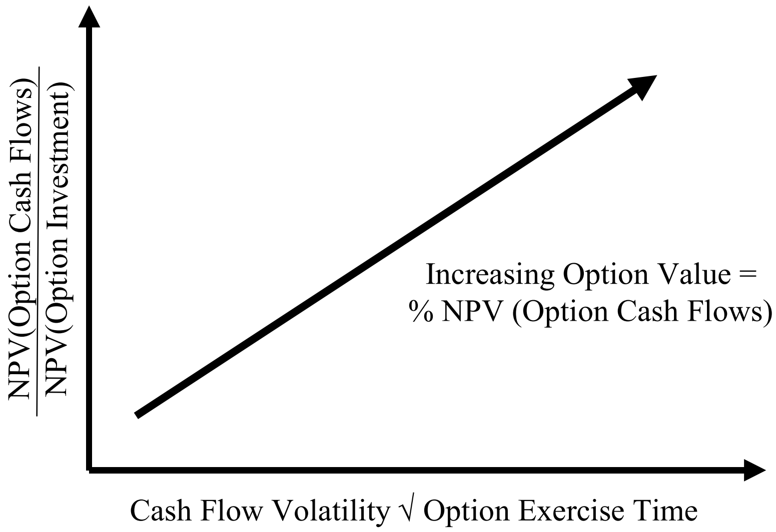

Fig. 2. Option value space.

returns, it is common to represent their impact in terms of changes of projected cash flows (Amram & Kulatilaka, 1999). In many cases, competitors acting first will decrease potential cash flows which will decrease the option value. As discussed later, it is often possible to construct alternative competitive scenarios to address this phenomenon.

Thus, options pricing models explicitly represent the effects of random variations of actual cash flows relative to projected cash flows. Risks that R&D does not develop viable technology options, or that viable technology options are not adopted for inclusion in product launches, or that competitors capture portions of the projected cash flows[2] are *not* inherent elements of options pricing models. These risks are independently represented in the *Technology Investment Advisor* as described later in this article. Sensitivity analysis and Monte Carlo analysis provide means to explore the impacts of imprecision of information regarding statistical properties of model variables.

S-Curve Maturity Models

Options pricing models provide an excellent means for estimating the value of the technology options that R&D creates. The option value can be viewed as the upper limit of what one should be willing to pay for these technology options. This quickly leads to question of what the R&D will actually cost.
This question is an element of a broader set of questions concerning how technology investments will translate into the downstream cash flows upon which the options pricing calculations are based. Investments in technology typically require significant time to mature, particularly in terms of their impacts in the marketplace. This maturation process is often characterized by S-curves, as shown in Figure 3 (Boer, 1999; Christensen, 1997; Foster, 1986; Roussel, Saad & Erickson, 1991).

While different authors use varying terms to define each stage of maturation, they all include the same stages. Boer (1999) characterizes incubation as a search for credibility; growth as coming at the expense of older products and technologies; maturity as growth at some multiple of GDP; and decline as gradual, with rates varying substantially by industry.

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[2] Legal actions may also preempt gaining projected cash flows via, for example, anti-trust regulations. Within the framework presented in this article, this possibility could be represented as a form of competition.

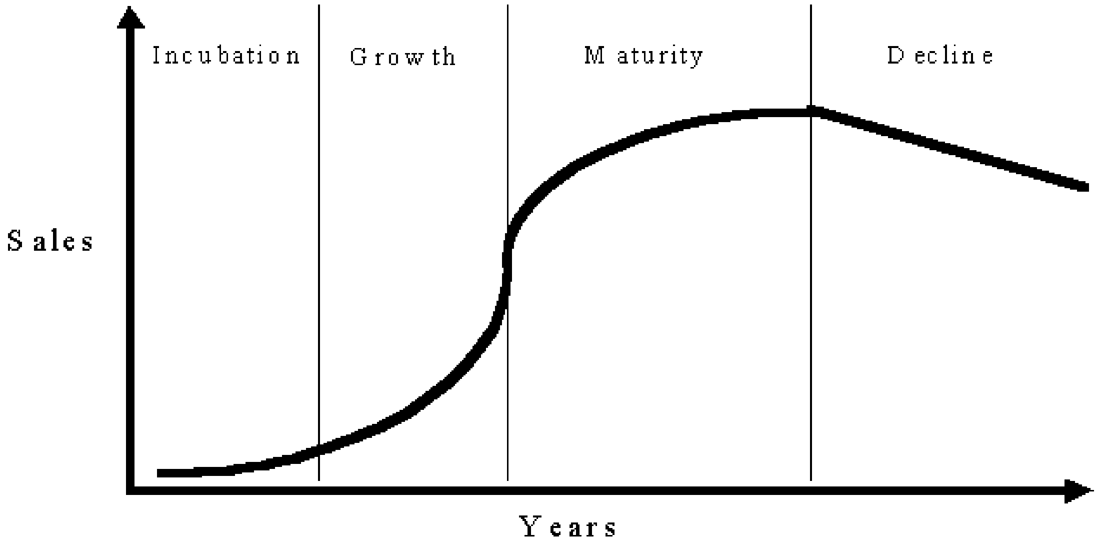

Fig. 3. Typical S-curve model.

Roussel (1984) discusses the stages of maturation in terms of:

- Time to commercialization
- Knowledge of competitive R&D
- Predictability (technical, reward, and R&D costs)
- Durability of competitive advantage

In general, time gets faster, knowledge increases, predictability increases, and durability of advantage decreases as one moves through the stages. Due to the decreased competitive advantage in the later stages, companies will often consciously transition from maturity to decline by launching new S-curves. These launches might involve derivative technologies or totally new technologies.

Christensen (1997), citing Foster's (1986) earlier work, characterizes technological innovation as a series of intersecting technology S-curves whereby new technologies emerge to surpass the performance of old technologies. Roussel, Saad & Erickson (1991) note that the impact of this replacement process varies considerably for three different types of technology:

- *Pacing Technologies* have the potential to change the basis of technological competition
- *Key Technologies* are embodied in products and processes, and are usually differentiated in leading companies
- *Base Technologies* are essential, but typically known to and practiced by all competitors

Innovation in pacing technologies can be viewed as resulting in totally new S-curves, while innovation in key technologies is more likely to yield derivative S-curves. The evolution of base technologies seldom is characterized as technological innovation.

While there are a variety of formulations of S-curve models (Young, 1993), the form advanced by Meyer (1994) has some attractive properties. Equation 4 describes the growth, S(t), over time of sales, profits, etc.

$$S(t) = S_o/\{1+ \exp[-(\mathrm{Ln}(81)/\Delta t)(t-t_m)]\} \tag{4}$$

where S_o is the saturation parameter, t_m is the midpoint, Δt is the number of time units between 10% and 90% of saturation, and 81 reflects the number of time units between 10 and 90.

One of the reasons this formulation is attractive is because it can be easily transformed to facilitate curve fitting via three-parameter linear regression models. It should be noted that fitting data may involve multiple, successive S-curves. In this case, either the data must be split into portions attributable to each curve, or multi-curve models can be defined, with three parameters per curve.

S-curve models provide valuable means for projecting the outcomes of R&D efforts. By adjusting S-curve parameters to particular industries and technologies, one can determine the series of intersecting S-curves that must be launched to achieve the cash flows upon which the option valuation is premised. One could also fit the series of S-curves to the projected cash flows and then determine the extent to which this series is feasible both technically and in terms of investment requirements. The needed investment can be "backcasted" from the number and timing of technology options required to achieve the desired cash flows.

Alternatively, one can begin by developing S-curve models based on bottom-up projections from on-going or proposed R&D efforts, carry the S-curve model outputs into the options calculations, and then determine the option value of these ongoing and/or proposed efforts. In this case, the investment analysis begins with projects and then determines what these projects are worth. In the earlier case, the analysis begins with cash flows sought, calculates the value of an option to gain these cash flows, estimates the number of technology options needed, and determines the R&D projects required to create these results.

Note that in either case, one needs to account for technology investments that do *not* create technology options, as well as options created that are *not* exercised. Some investments lead to conclusions that particular technologies will not meet product/process requirements. Other investments lead to viable technology options that no longer make sense when it comes time to exercise these options. Determination of the number of projects needed to yield the desired cash flows must take these two winnowing processes into account.

Production Learning Models

In parallel with growth and maturation of technologies and markets characterized by S-curve models, experience and skill in production processes increase. This learning results in decreasing unit production costs that enable increased margins and/or decreased prices to provide competitive advantage. Production learning models provide a means for representing this learning process.

Hancock & Bayha (1992) discuss the classic learning equation:

$$Y = KX^{-A} \tag{5}$$

where

Y = the time per cycle
K = the time for the first cycle
X = the number of cycles
A = a constant determined by the learning rate.

With this equation, every time X is doubled, the value of Y decreases by a fixed percentage, e.g., a 90% curve is such that every time the number of cycles double, Y is 90% of the previous value. Hein & Compton (1992) also discuss the classic learning equation and provide a variety of references on the broad applicability of this equation, as well as the underlying learning phenomena.

For production processes, the most common curve is an 80% curve — in this case, A = 0.32192. Also Y is usually expressed in terms of cost per unit or time per unit, and X is the cumulative number of units produced. Hancock & Bayha provide a table of data ranging from 60–90% depending on the industry, e.g., automobiles vs. airplanes. Lee (1987) reports that 80% learning curves are typical for production processes that are labor intensive. The typical range is 60–95%.

Production learning models can be used to predict the unit costs of the products sold to achieve the projections derived from the S-curve models. The S-curve models, in this case, are usually employed to project total units sold. Revenues are then calculated by multiplying number of units sold times the sum of unit costs and profit margins.

Alternatively, using the S-curve models to project revenues results in units sold equaling revenue divided by the sum of unit costs plus profit margins. However, since unit costs depend on units sold — via the learning model — this approach requires solving simultaneous nonlinear equations. Consequently, it is much easier to use the S-curve models to project units sold.

The decreased costs due to production learning provides opportunities for increased profit margins. However, this possibility depends strongly on the competitive environment. In general, there are three ways to take advantage of projected decreased costs:

- Project higher margins — by keeping prices fixed
- Project lower prices — by keeping margins fixed
- Project some combination of higher margins and lower prices

The choice among these alternatives depends on one's competitive position, which leads to discussion of competitive scenarios.

Competitive Scenarios

The primary competitive issues concern projecting market shares and profit margins for new product launches and derivative product launches. Four competitive scenarios appear sufficient to describe the alternative outcomes:

- No competition
- 1st In and Others Follow
- 2nd In and There Is Only One Follower
- 2nd In and There Are Many Followers

For example, consider the alternative choices for how to take advantage of decreased unit costs. With the "No Competition" and perhaps the "1st In" scenarios, one can often maintain prices and thereby increase margins, although market share may eventually be lost to followers if prices are not decreased to some extent. However, a "2nd In" competitor may need to decrease prices significantly to capture market share, especially if there are multiple followers.

Competitive scenarios can be used to represent the impacts of competition in terms of feasible ranges of market shares and margins, typically based on company and/or industry experience. These ranges also depend on strategy and technology advantages. A strong brand name plus proprietary technology will enable achieving market shares and margins toward the upper ends of these ranges. Lack of such advantages will push likely shares and margins down.

Choices among the above competitive scenarios, in combination with specifications of strategy and technology advantage, determine feasible limits for market shares and profits margins, based on either company or industry experience. One might for example, project share and margin as the midpoints between the lower and upper bounds dictated by scenario/advantage choices. However, there may be many reasons why such midpoints are unreasonable. Unlike the other models in the overall framework presented here, the company/industry-specific nature of competitive scenarios makes providing recommended ranges for key market variables more useful than attempting specific projections of these variables.

Model Interactions

Figure 4 shows the interactions of the four models — options pricing, S-curve, production learning, and competitive scenario — and how these interactions vary depending on what aspects of the overall set of models are being employed. One can start at either end of this approach. One can use the S-curve and production learning models to project the financial information, which feed the option pricing model. Or, one can start with the option pricing model to determine the option value of a given cash flow, and then use the S-curve and production learning models to generate sales and cash flows, as well as "backcast" required R&D budgets to achieve these outcomes.

Note that Figure 4 indicates the Net Option Value as the central output of this set of models. In the absence of a contingent downstream investment decision, the analysis reduces to more traditional discounted cash flow methods. In this case, the output would be the usual Net Present Value. When applying this model-based approach to a portfolio of investments, it is quite likely that some investments will represent options and others will not. As indicated in later discussion, the *Technology Investment Advisor* is designed to handle such differences.

The inputs to the S-curve model include parameters for saturation, inflection, and time scale. For multiple product launches, the S-curve model also requires criteria for launching product derivatives, including parameters that characterize "descendent" S-curves. The S-Curve model projects either total market revenue or total market units sold each year, depending on whether production learning is being used. The production learning model uses the number of units sold each year and the initial unit cost to project the unit costs for each year.

Multiplying the unit cost for each year by the number of units yields the operating costs for each year. Subtracting the operating costs from the total revenue yields the free cash flow estimates needed by the option pricing model. The number of product launches is used to determine the number of technology options required, and subsequently the required R&D budgets. These budgets are coupled with capital costs and other investments to yield the total investment, or exercise price, needed by the options pricing model. The combination of free cash flow and total investment enables determining the Net Option Value.

Note that Figure 4 indicates several paths for data flow and calculations. For instance, S-curve models can be used to project revenues or units. As another example, production learning can be driven by your production volume, or by the total market production volume — the former applies when production technology is proprietary, while the latter holds when all manufacturers buy the same production equip-

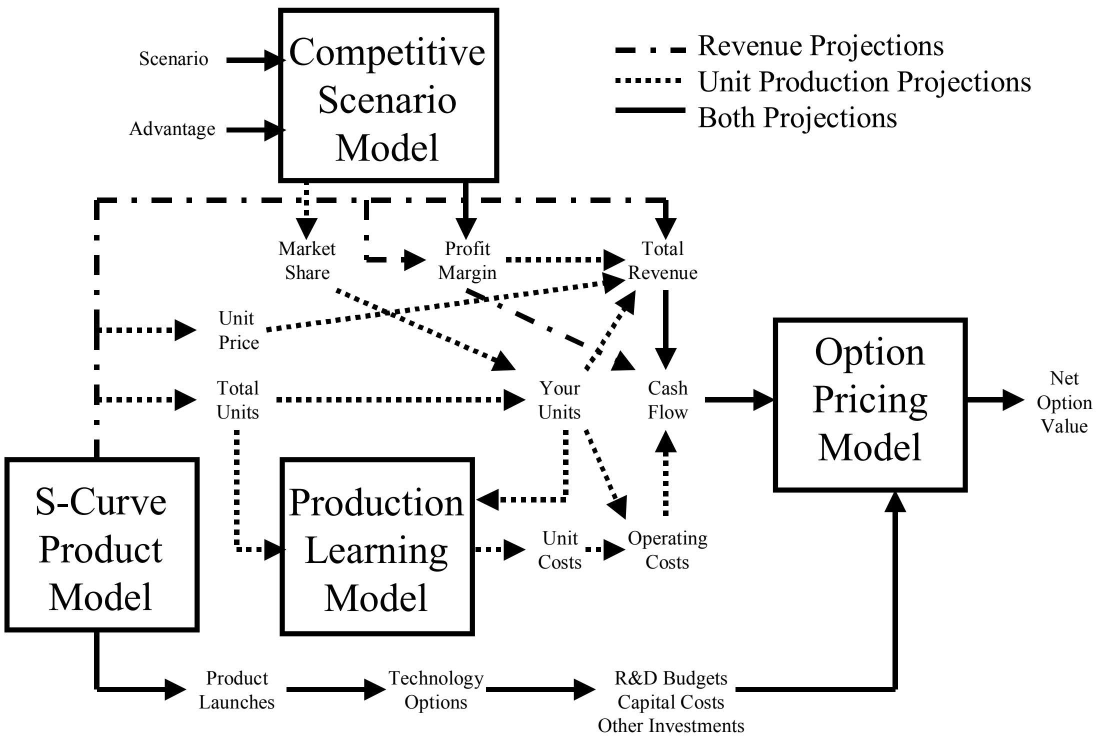

Fig. 4. Interactions of models.

ment from common vendors. For any particular analysis, one must decide which data flows and calculations are most appropriate.

Figure 4 also indicates the impacts of the competitive scenario model. As explained earlier, choices of competitive scenario, strategy advantage, and technology advantage results in projected upper and lower bounds for market shares and profit margins. One can split this difference or project other values of share or margin, depending on the particular competitive situation. It is easy to imagine that more sophisticated competition models, e.g., based on game theory, may be feasible and warranted for some applications. However, such models would, by no means, be as “off the shelf” as the other models discussed in this article.

It is useful to consider how the integrated set of models depicted in Figure 4 address uncertainties, risks, and information precision. Random variations of projected cash flows are inherent to options pricing models. The probabilistic nature of R&D — that is, whether viable options are created and whether they are adopted — are represented by technical and market success rates, respectively. The risks of competition for market share and margins — as well as other forces that could undermine share and margin — are represented via competitive scenarios. Of course, all of the parameters associated with the models in Figure 4 are only estimates and are subject to imprecision. The impact of this imprecision can be assessed via sensitivity analysis and Monte Carlo analysis as illustrated in the following sections.

TECHNOLOGY INVESTMENT ADVISOR

The above model-based approach to technology strategy formulation and evaluation is embodied in the *Technology Investment Advisor* (TIA) shown in Figure 5 (ESS, 2000). Use of this software tool involves

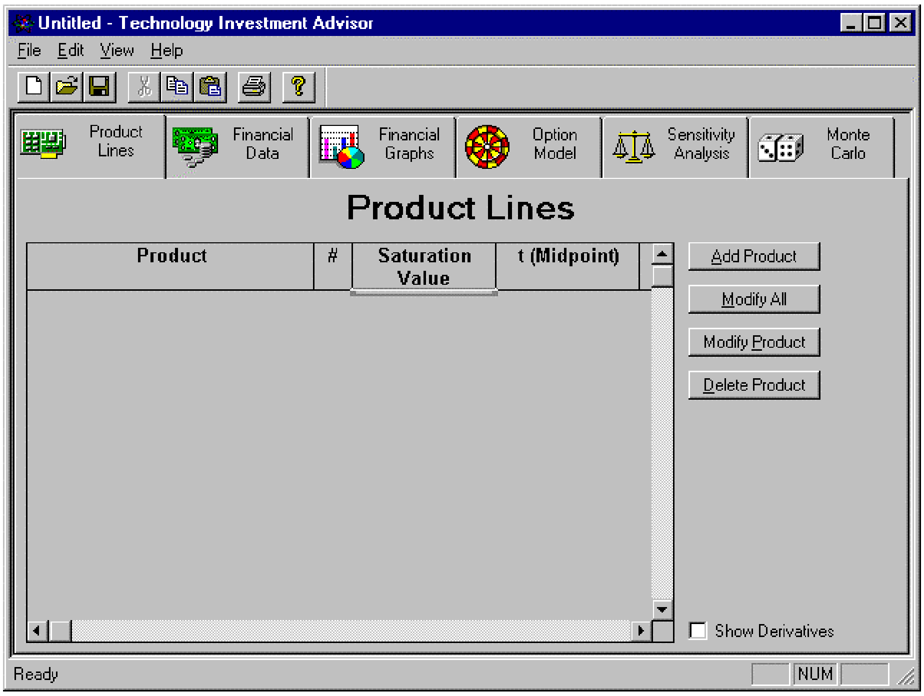

Fig. 5. TECHNOLOGY INVESTMENT ADVISOR.

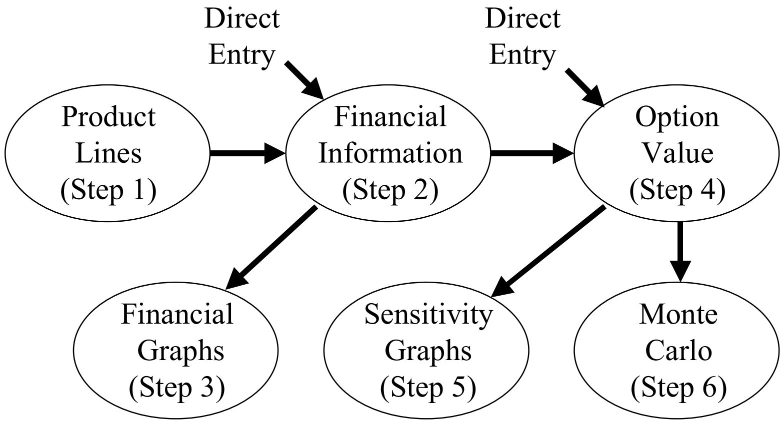

Fig. 6. Concept of use for TECHNOLOGY INVESTMENT ADVISOR.

performing all or a subset of the following six steps:

- Formulation of product line models
- Generation (or input) of projected financial statements
- Review of graphical depictions of financial statements
- Determination of option values of technology investments
- Assessment of sensitivity of option values to key variables
- Assessment of impacts of uncertainties via Monte Carlo analysis

Concept of Use

The TIA concept of use is summarized in Figure 6. One can use any or all steps and associated models. For example, one can directly enter financial information into the spreadsheet associated with the options pricing model (Step 4). Alternatively, one can "pull" this information from projected financial statements (Step 2). The inputs to this step can come from direct entry — perhaps cut and pasted from a spreadsheet tool such as Excel — or be pulled from the product line models (Step 1). Steps 3, 5, and 6 enable viewing results, assessing their sensitivity, and determining impacts of uncertainties, respectively.

This concept of use provides considerable flexibility. One can use any or all steps which, in effect, means that any or all models can be employed. This enables beginning with a very simple representation and building a more comprehensive representation as intuition and insights are gained.

Typical Applications

The *Technology Investment Advisor* has been applied to a wide range of technology strategy problems. Several examples are briefly described here. The next section presents a detailed example.

One class of applications concerns investing in research in, for example, physical sciences for the purpose of creating product innovations in the semiconductor and electronics markets. Such applications involve in-depth consideration of R&D project costs and success rates, as well as detailed examination of likely learning effects. Comparisons of model-based projections with independent financial analyses can also be important to provide convergent evidence of the validity of assumptions.

Another class of applications concerns evaluation of technology portfolios for process improvements, for instance in aircraft manufacturing. These applications involve characterizing improvement projects in terms of initial investments and contingent investments for the purpose of saving process costs. These

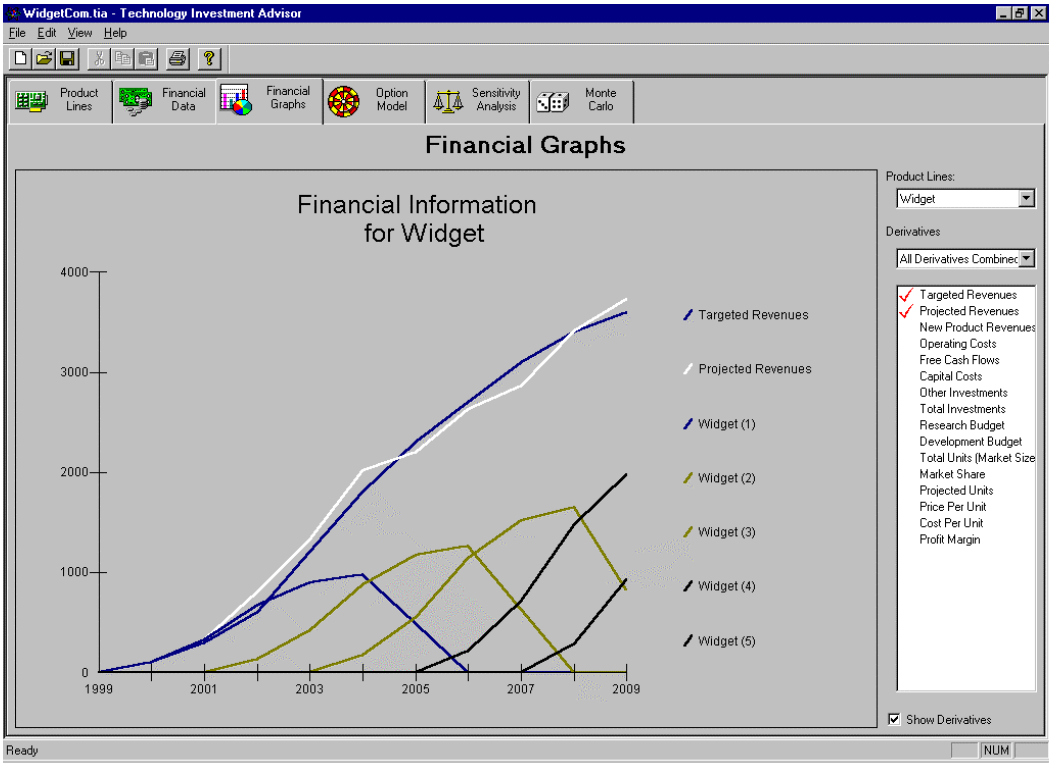

Fig. 7. Targeted and projected sales of advanced widgets.

savings tend to be very dependent on the volumes of work performed by processes. Uncertainties regarding these volumes tend to strongly affect investment risks.

Yet another class of applications concerns valuation of government investments in technologies for lowering the costs of meeting mission requirements (Rouse & Boff, 1999). Government R&D investments often serve the purpose of providing industry technology options, which they may exercise in proposing development projects to the government. The free cash flow resulting from exercising such options results in reduced acquisition costs for the government.

In general, any investment problems that involve upstream investments for the purpose of creating contingent downstream investment opportunities are good candidates for use of the approach described in this article (Rouse, 2000). When there are no contingent investment decisions, traditional discounted cash flow methods apply. It is quite common for an investment portfolio to include some investments characterized in terms of Net Option Values and others by Net Present Values. Both types of investments can be represented using the *Technology Investment Advisor*.

AN EXAMPLE

Widget.Com wants to develop a new advanced widget. Their goal is to sell the number of advanced widgets per year shown in Figure 7 — labeled Targeted Revenues. Units sold are in thousands and revenue is the same because widgets sell for $1 a piece.

The first step is to develop an S-curve model of this sales stream. The best-match S-curve has a saturation value of 1,000,000 units/year, an inflection time of 1.5 years, and a duration of 3.0 years. In addition, product derivatives (i.e. new versions of the advanced widget) need to be launched every 2 years to keep the market interested in the widget. Widget.Com expects each subsequent derivative to be 30% more popular than its predecessor. Once a derivative reaches 95 percent of its saturation level, Widget.Com believes sales will decline by 50% per year for that version of the advanced widget. Based on the above information, they project the sales from the whole family of S-curves shown in Figure 7 — labeled Projected Revenues.

To determine the R&D investment required for advanced widgets, the company begins by reviewing past experience with new products. These data show that Widget.Com requires three technology options to find one to exercise in launching a new product (i.e. 33% market success rate) and that it takes four R&D projects to generate one proven technology option (i.e. 25% technical success rate). Thus, Widget.Com needs to invest in twelve R&D projects to ensure at least one successful product launch. Past experience also indicates each R&D project costs $30,000 per year for the two years prior to the product launch. Widget.Com also expects each new product launch to cost $200,000 per year for two years.

Derivative product launches also require investment. Fortunately, derivative products of a successful product are not as expensive to develop. It still takes four R&D efforts to create a proven technology option (i.e., 25% technical success rate), but each option is expected to make it to the market. In addition, derivatives are not as expensive to develop and can be launched with an investment of $30,000 per year for two years. (Remember, derivatives are launched every two years in this example.) Adding the costs of research to those for development associated with initial launch and those for derivative launches yields the investment profile shown in Figure 8.

With the S-curve model specified, attention now turns to modeling production learning and its impact on operating costs. From past experience, Widget.Com estimates that the cost to create the first widget is

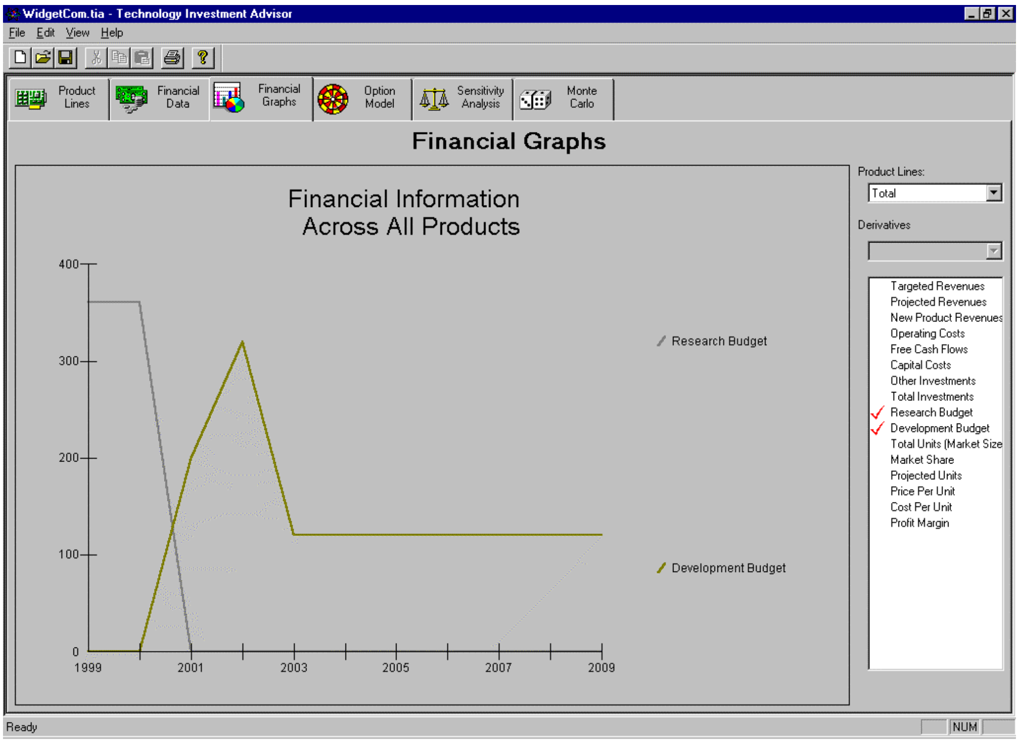

Fig. 8. Costs of R&D, initial product launch, ad derivative product launches.

about $2 and that the learning rate is about 90%. These parameters in conjunction with the projected numbers of units sold yield projected units costs of $0.99 for the first year, $0.80 for the second year, and so on, as shown in Figure 9.

Incorporating the results of the production learning yields the revenue, cost, and cash flow projections shown in Figure 10. The cash flow projection in Figure 10 and the investment projection from Figure 8 serve as inputs to the option pricing model. Based on an assumed discount rate of 12%, a risk-free rate of return of 5.5%, a two-year period before the option can be exercised, and 40% volatility of projected cash flows, the results in Figure 11 indicate an option value of $5,945,620 and a Net Option Value of $5,263,710 when the Net Present Value of the research investment is subtracted.

This obviously appears to be a very attractive investment. However, this assessment is based on very tenuous assumptions. The effects of production learning, coupled with holding prices fixed, yields an 86% profit margin by the tenth year. This would only be possible without competition and, with such margins, competition will most certainly emerge.

To represent this possibility, the competitive scenario is changed from “No Competition” to “1st In — Others Follow”. Assuming strong strategy advantage and moderate technology advantage yields market share and profit margin ranges from which the share and price profiles shown in Figure 12 emerge. The option value consequently drops precipitously to $19,280 and the Net Option Value becomes negative at ($662,830). Clearly, potential competition appears to eliminate most of the value of this investment.

Nevertheless, this opportunity represents 30–40% profit margins in a growing market. Such growth suggests that the assumption of zero terminal value at year 10 is much too conservative (Boer, 1998, 1999). Assuming that the free cash flow of roughly $200,00 in year 10 continues in perpetuity, without growth after the horizon year, yields a terminal value of $1,666,667. This changes the option value to $216,980, but the Net Option Value remains negative at ($465,130). Nevertheless, it would be difficult to justify a higher terminal value.

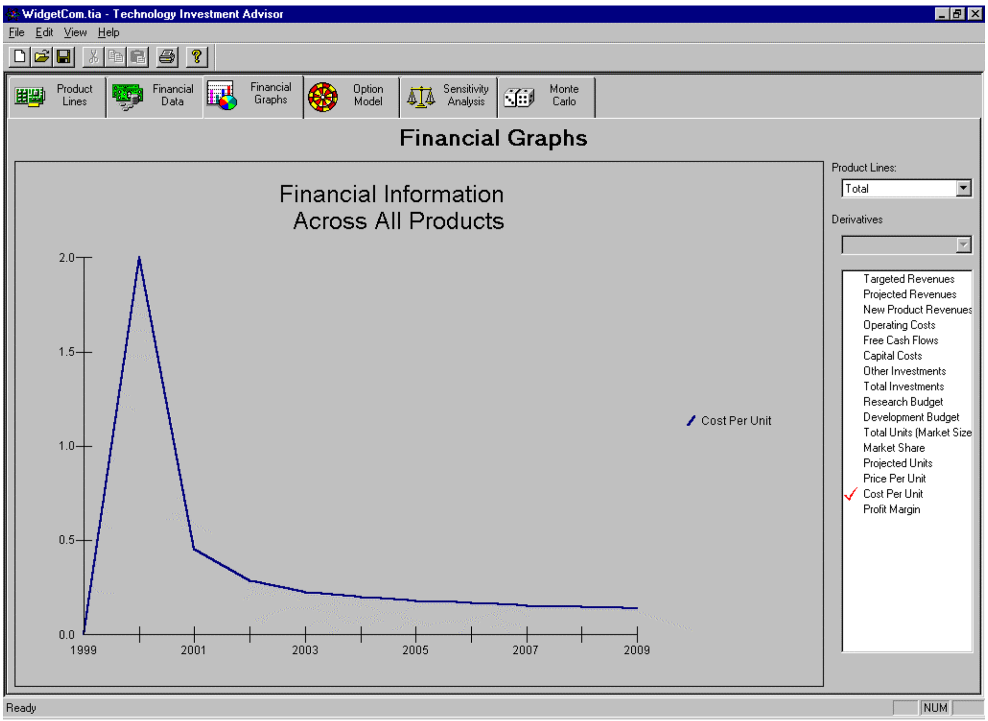

Fig. 9. Change of unit production costs due to learning.

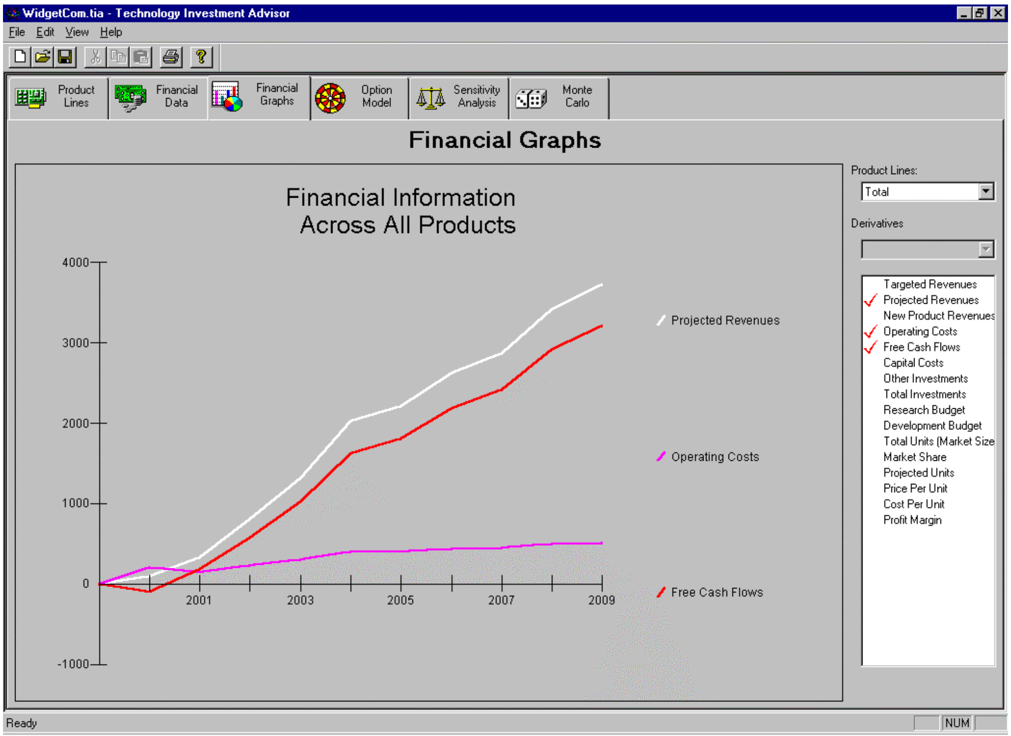

Fig. 10. Projected revenues, costs, and cash flows.

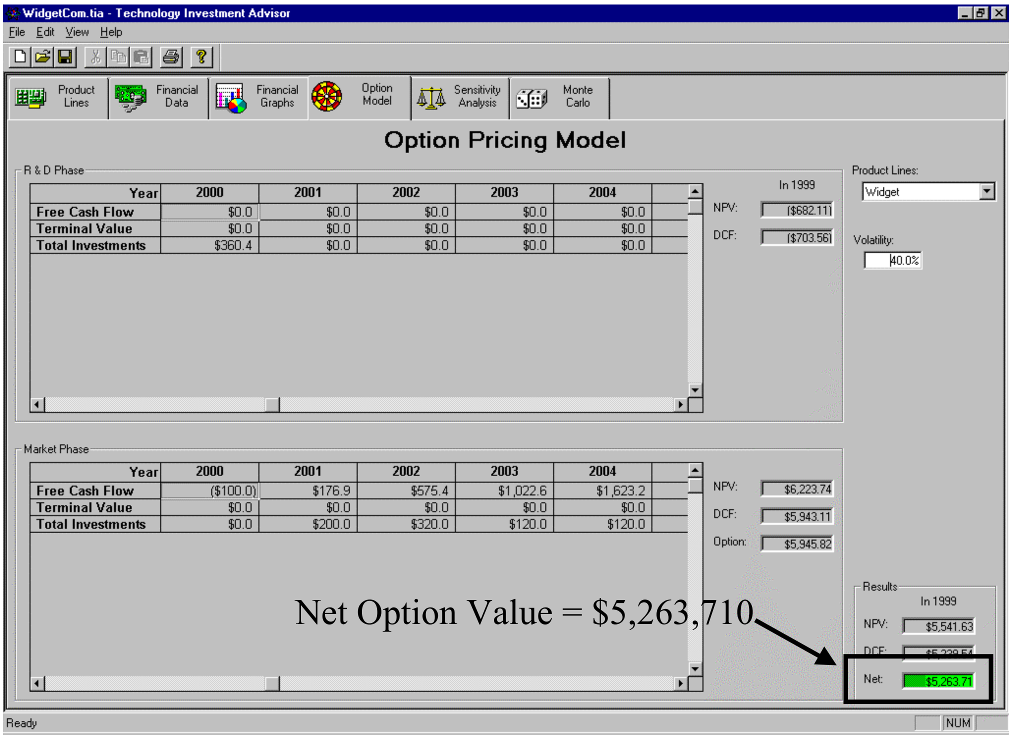

Fig. 11. Options pricing model and net option value.

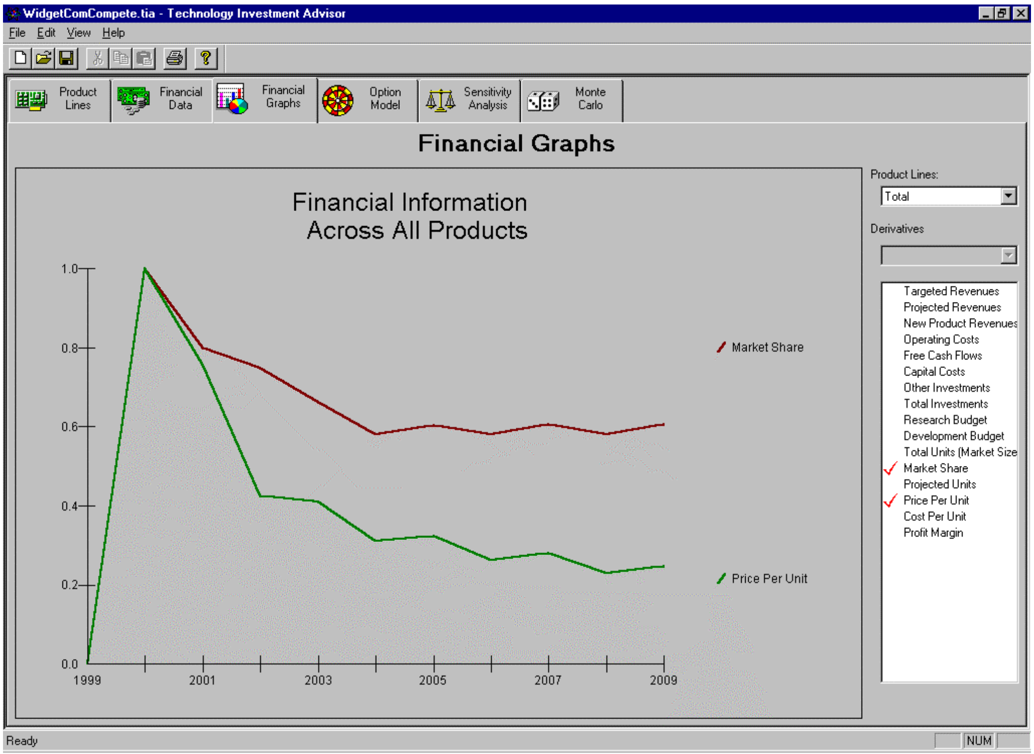

Fig. 12. Market share and price per unit for "1st In - Others Follow" scenario.

Further, the problem is not really the option value, but the Net Option Value. The main determinant of the negative Net Option Value is the high R&D costs, especially the research costs. Only 1 in 12 projects succeeds in transitioning technology to the marketplace. With each project requiring two years and costing $30,000 per year, the total research costs are $720,000 to "purchase" a viable technology option for getting the advanced widget into the market. The development costs are also high, but these costs are part of the exercise price, not the option price.

Assumptions made about rates of technical and market success for R&D projects, as well as the budgets for these projects, are subject to significant uncertainty. To explore the impact of this uncertainty, a Monte Carlo analysis was performed leaving all model parameters fixed except for budgets for research, initial development, and derivative development. The means assumed for these budgets were set as 50% of the original values, and the standard deviations were set as 20% of the original values. The results are shown in Figure 13.

The average Net Option Value is $171,700, the standard deviation is $215,700, and the probability that the Net Option Value exceeds zero is 0.78. Clearly, the assumed success rates and budgets are very important. The success rates need to be doubled or the budgets halved, or some combination of both. One approach to accomplishing this goal is to adopt a multi-stage approach to project funding so that only the more likely to succeed projects make it through the investment "funnel" (Cooper, Edgett & Kleinschmidt, 1998; Rouse, 2000).

Interestingly, reducing investment costs by 50%, on average, has a more positive effect than doubling the size of the market. The investment costs are simply too high for the intensity of the competition in this hypothetical market. This competition strongly limits margins as all competitors make it down the learning curves and cut prices to gain or maintain market shares. Of course, variations of other assumptions would be explored before this assessment was accepted as definitive.

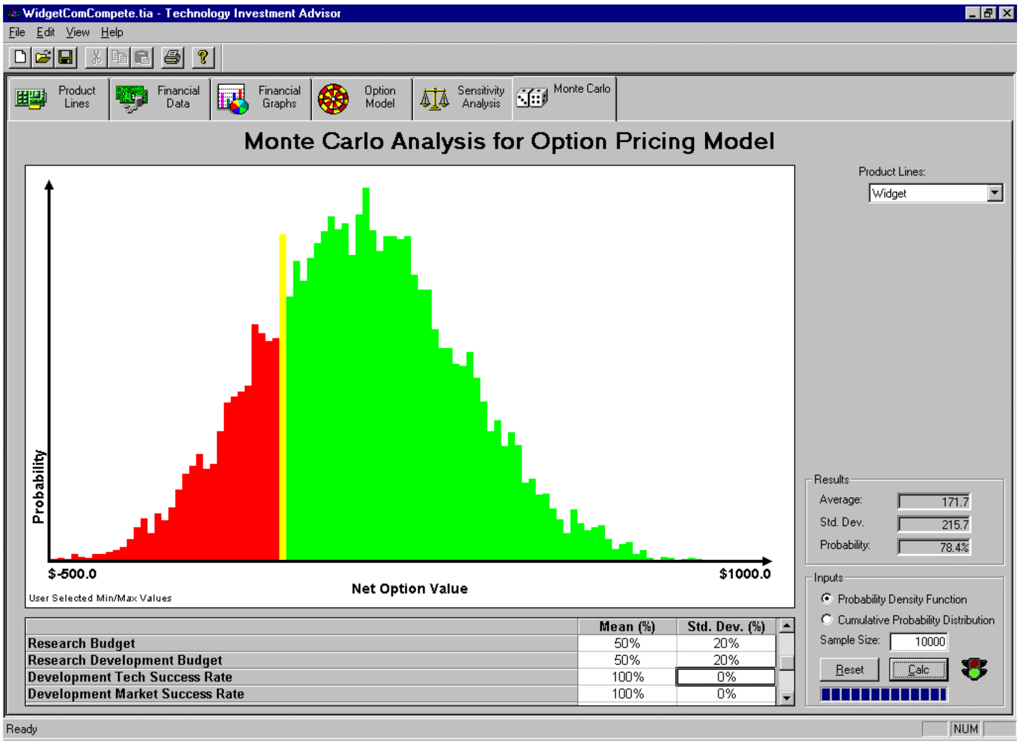

Fig. 13. Distribution of net option values.

CONCLUSIONS

This article has shown how options pricing models, S-curve maturity models, production learning models, and competitive scenarios can be inter-related to approach technology strategy issues in an integrated manner that enables rigorous consideration of the uncertainties and contingent decisions inherent with R&D investment decisions. The options-based approach recognizes the true nature of most long-term technology investment decisions. The *Technology Investment Advisor* supports application of this approach.

The options-based approach enables a new philosophy toward R&D organizations. Specifically, the role of an R&D organization — especially for longer-range research — is to provide the enterprise with technology options. In contrast, the role of the business units is to decide whether or not to exercise these technology options. Some and perhaps many options will never be exercised, at least not for their original purpose. Nevertheless, there is substantial value in owning such options. The *Technology Investment Advisor* helps one to ascertain this value.

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